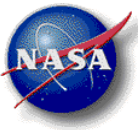


# **Diagnostics and Prognostics of Electro-Mechanical Actuators**

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**Edward Balaban, NASA Ames Research Center**

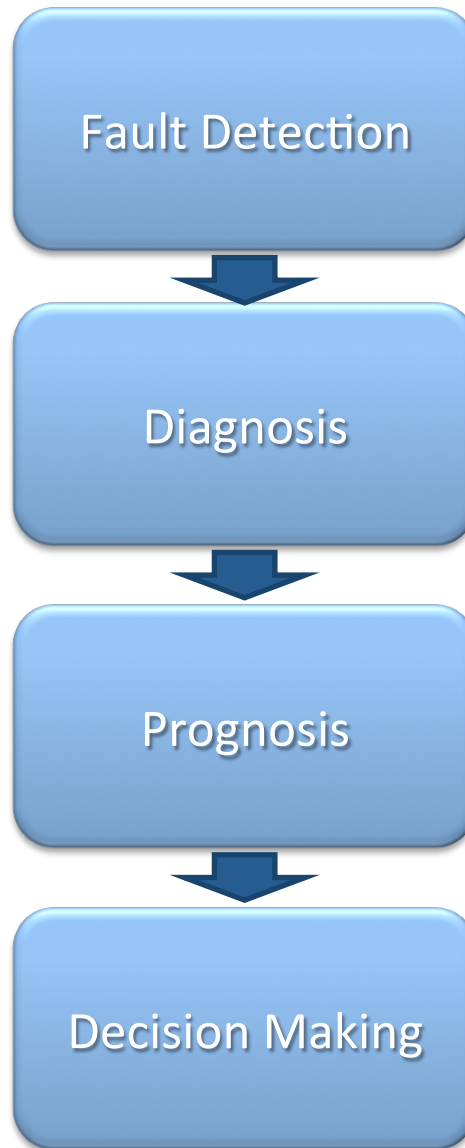


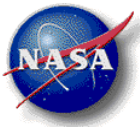
# Team Members

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- ☐ Edward Balaban
- ☐ Sriram Narasimhan
- ☐ Abhinav Saxena
- ☐ Indranil Roychoudhury
- ☐ Michael Koopmans (student intern)
- ☐ Zachary Ballard (student intern)
- ☐ Sterling Clarke (student intern)

- ☐ NASA Ames Diagnostics and Prognostics Group
- ☐ EMA health management - motivation and approach
- ☐ Data collection
- ☐ Diagnostic system development
- ☐ Prognostic system development
- ☐ Laboratory experiments
- ☐ Flight experiments
- ☐ Summary



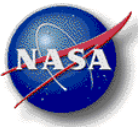


- Areas of work
  - Diagnostic systems
  - Prognostic systems
  - Decision-making systems
  - V&V techniques
- Components and systems studied
  - Electro-mechanical actuators
  - Power electronics
  - Batteries
  - Composite structures (in collaboration with Stanford University)
  - Cryogenic refueling systems (in collaboration with NASA Kennedy)
- Methods
  - Discrete model-based diagnosis - Livingston
  - Hybrid (discrete/continuous) diagnosis – HyDE
  - Model-based prognosis – particle filters, Kalman filters
  - Data-driven prognosis – neural networks, Support Vector Machines, Gaussian Process Regression
  - Decision-making – stochastic optimization methods, game-theoretic methods, dynamic programming

# Diagnostics and Prognostics Group (continued)

- Test facilities
  - EMA testbeds
  - ADAPT (Advanced Diagnostics and Prognostics Testbed) – aircraft power distribution
  - Electrical battery aging testbed
  - Electronics aging testbeds (for MOSFETs, IGBTs, and capacitors)
  - An environmental chamber (temperature, pressure, and humidity)
- Test vehicles
  - K11 planetary rover prototype
  - Edge 540 UAV (NASA Langley)
  - UH-60 Blackhawk helicopters (US Army at NASA Ames)





# Motivation for EMA Health Management

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- EMA are becoming a component critical to aircraft and spacecraft safety
- Performance data on EMA, both laboratory and in-flight, is scarce
- A variety of fault types can occur (discrete/continuous, abrupt/incipient) in a variety of subsystems (mechanical, electrical, control system, or sensor).
- We need to be able to diagnose faults quickly and accurately, to enable prognosis and mitigation
- We believe that collecting and testing on high-quality nominal and fault-injected data is essential to developing effective EMA health management systems

- Collect data on nominal and faulty Electro-Mechanical Actuator (EMA) performance
- Develop fault-detection and fault-propagation models
- Develop diagnostic systems
- Verify models and validate diagnostic systems using laboratory and field data sets
- Develop and evaluate model-based prognostic health management (PHM) systems
- Integrate with other aircraft subsystem PHM modules and a high-level vehicle health reasoner



# Nominal and fault modeling

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- Fault analysis
- Lubricant effects modeling
- Micro-scale mechanical modeling
- Wear modeling
- Winding shorts modeling
- Functional system models

# Experimental Data Collection

## Capabilities:

- 5 metric ton load capacity
- Accommodation of test actuators of various sizes and configurations
- Custom motion and load profiles

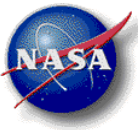


## Sensor Suit:

- Vibration
- Load
- Temperatures sensors
- High-precision position sensors
- Current sensors

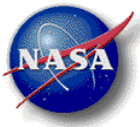
# The FLEA (Flyable Electromechanical Actuator)

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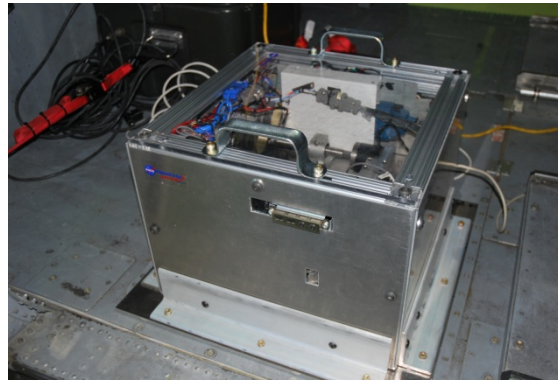
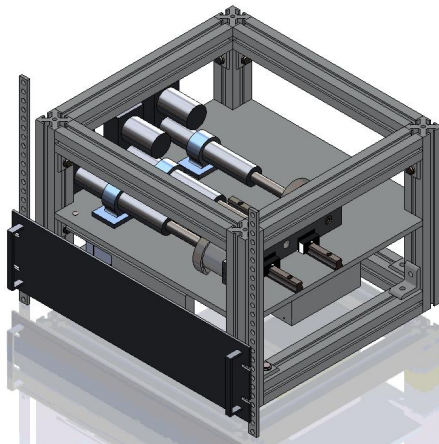
- Allows diagnostic and prognostic experiment execution in realistic conditions
- Designed to function as an unobtrusive secondary payload
- No aircraft modifications are required
- Experiments can be done during virtually any flight opportunity
- Designed to be quickly adaptable to different types of aircraft
- **Faults can be injected without endangering the host aircraft**

# The hardware



## Major hardware components

- Two test actuators
- Load actuator
- Magnetic coupling system
- Motion controller
- Central computer
- DAQ system
- Sensors
- Data storage system

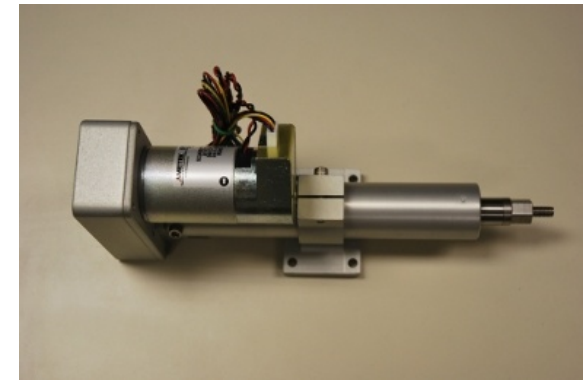


## Sensor suite

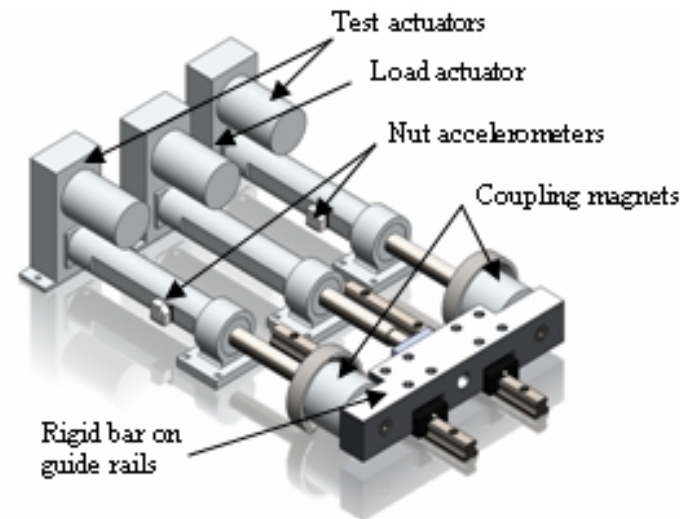
- High Speed (20kHz)
  - Accelerometers
- Low speed (1kHz)
  - current sensors
  - voltage sensors
  - position sensors
  - temperature sensors
  - load cell

## Major software components

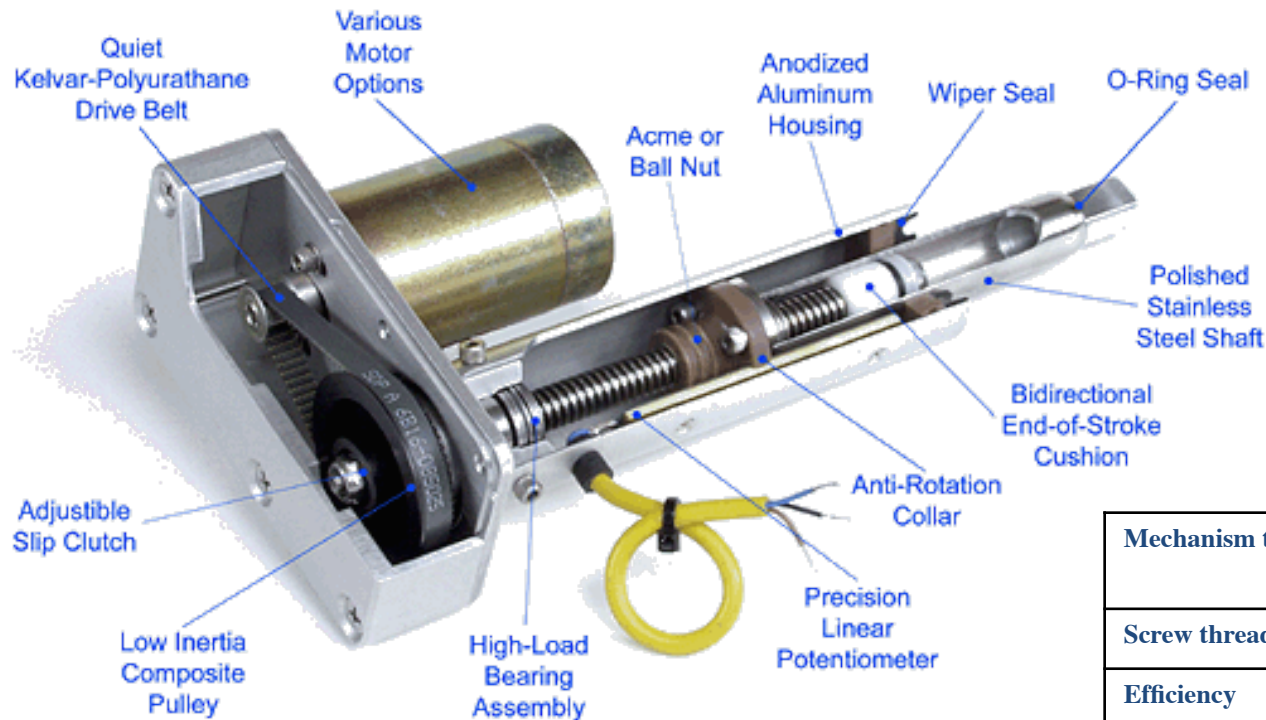
- Control system
- GUI
- Signal processing and data extraction
- Diagnostic system
- Prognostic system
- Experiment recording and data archival system



- An aircraft actuator is selected to be “mimicked”
- FLEA operates in parallel with the selected actuator, executing the same motion and load profiles
- Load profiles are calculated from aerodynamic data and scaled down for the FLEA range, if necessary
- One test actuator is kept nominal, the other one is fault-injected
- Load path can be switched in-flight from the nominal test actuator to the fault-injected one, via the magnetic coupling

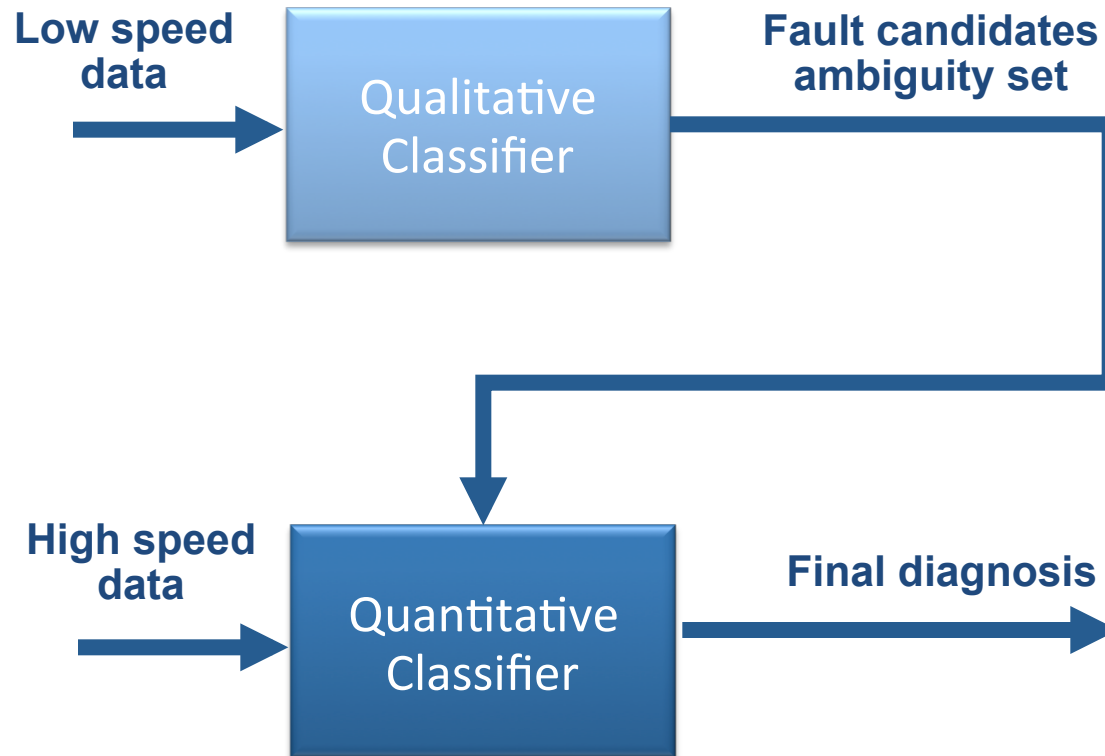


# Test Articles – UltraMotion Bug Actuators



<b>Mechanism type</b>	Ballscrew with a DC electric motor
<b>Screw thread pitch</b>	0.125 in/rev
<b>Efficiency</b>	98%
<b>Dynamic load</b>	5000 lb*in/sec (100% duty cycle)
<b>Motor stall torque</b>	41.3 oz/in
<b>Motor no-load speed</b>	102.5 rev/sec
<b>Motor stall current:</b>	8.11 amps
<b>Motor no-load current:</b>	0.16 amps

# Hybrid Diagnostic System

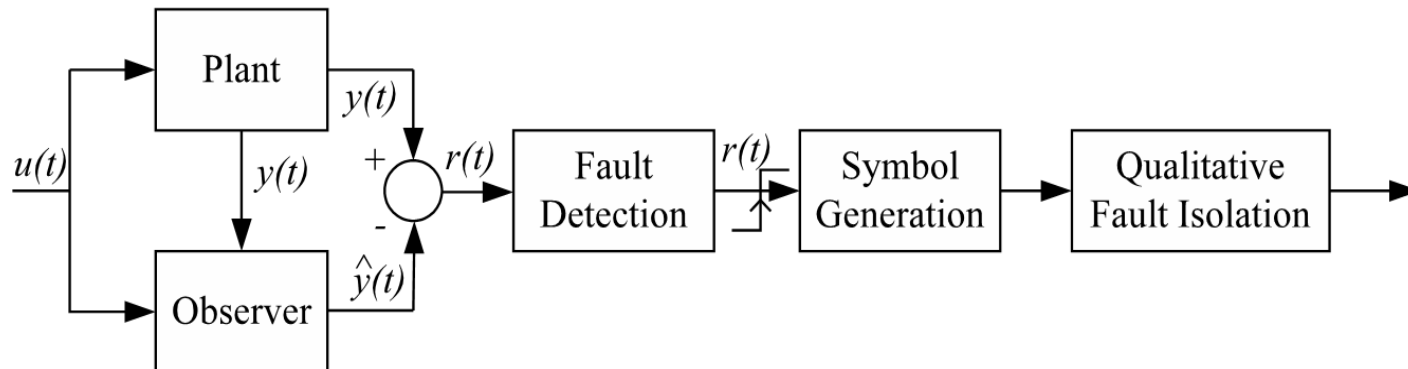


- Hybrid model / feature-driven approach
- Qualitative analysis on low speed data to reduce the possible fault set
- The reduced fault set disambiguated by looking for specific features in high speed data
- Runs continuously, updating its belief about the system health as more data becomes available



# Hybrid Diagnostic System (more details)

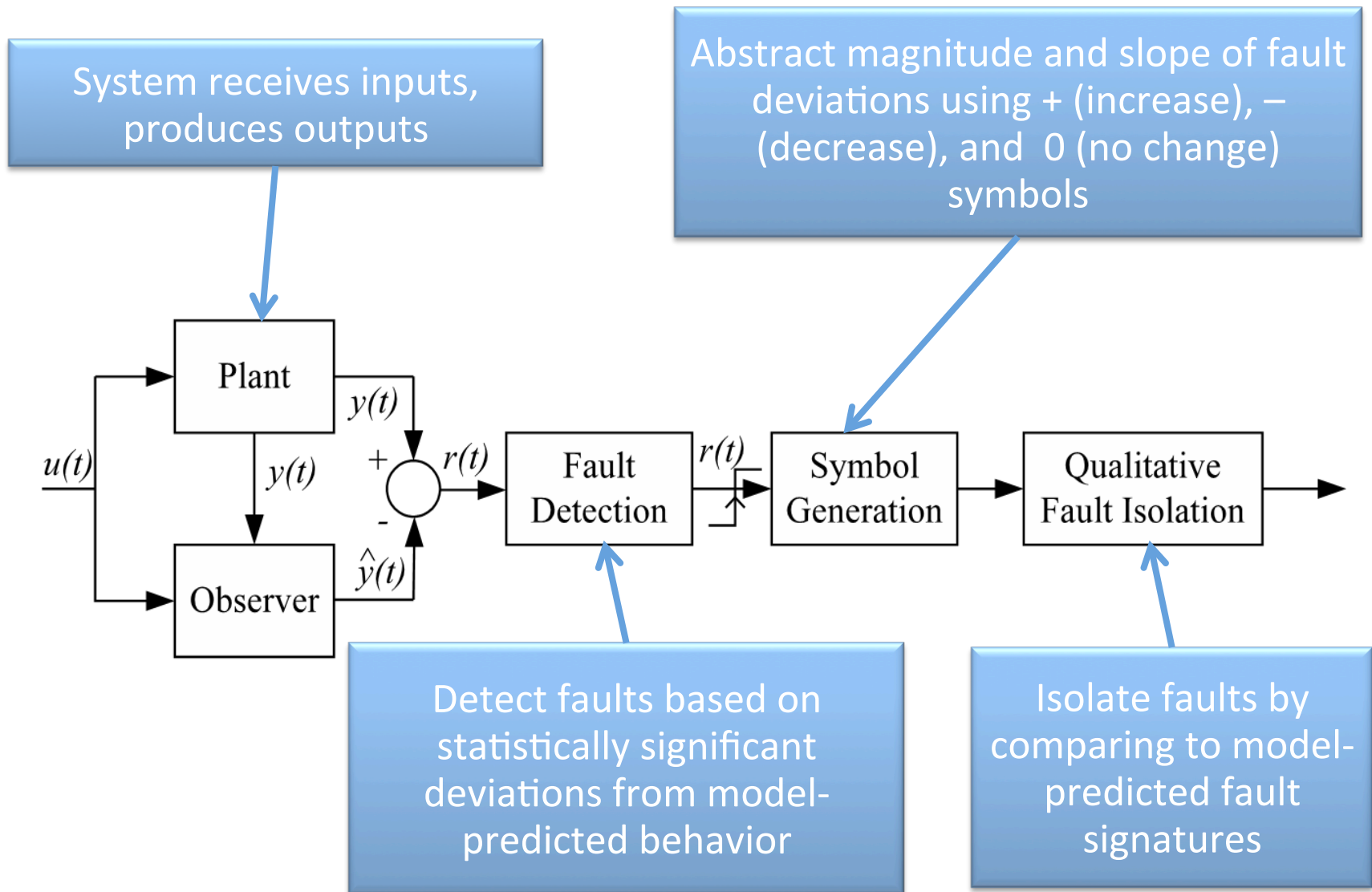
- **Qualitative analysis**
  - Qualitative signatures of fault derived from model as well as data from faulty runs.
  - An observer uses differential equations to track plant behavior
  - Qualitative symbols generated when predicted behavior (from observer) is not consistent with actual behavior (sensor data)
  - Comparison of symbols and signatures results in reduction of possible fault set



- **Disambiguation**
  - Features selected based on diagnosability analysis of qualitative approach
  - Features specific to selected ambiguity group

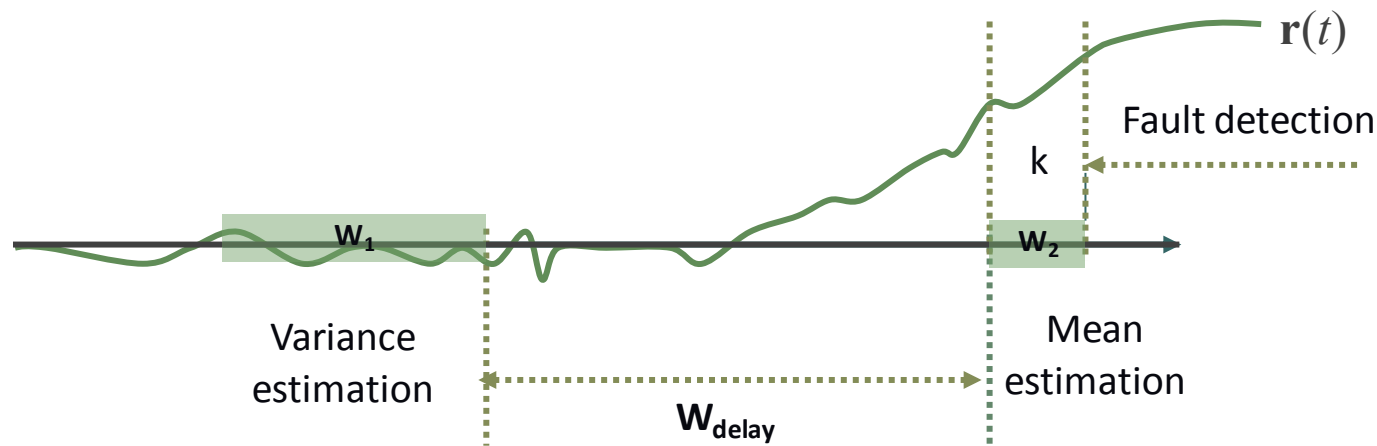


# Qualitative Fault Diagnostic Architecture



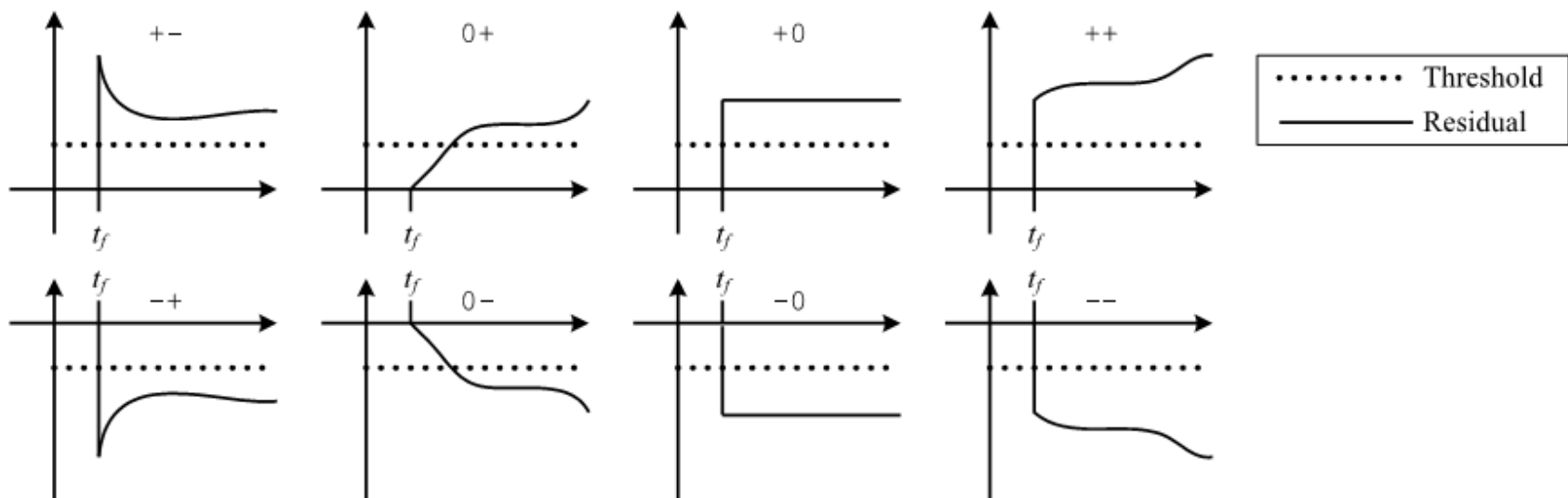
# Fault Detection

- For each sensor, residual  $r(t) = y(t) - \hat{y}(t)$
- Ideally, residual is zero, use Z-test to determine if nonzero residual is statistically significant
- Use set of sliding windows
  - $W_1$  computes variance of nominal residual
  - $W_2$  computes mean of residual at time  $k$
  - $W_{\text{delay}}$  ensures computation of variance does not include samples from after fault appearance
- Compute thresholds using Z-test and selected confidence intervals
  - Residual mean outside thresholds implies fault



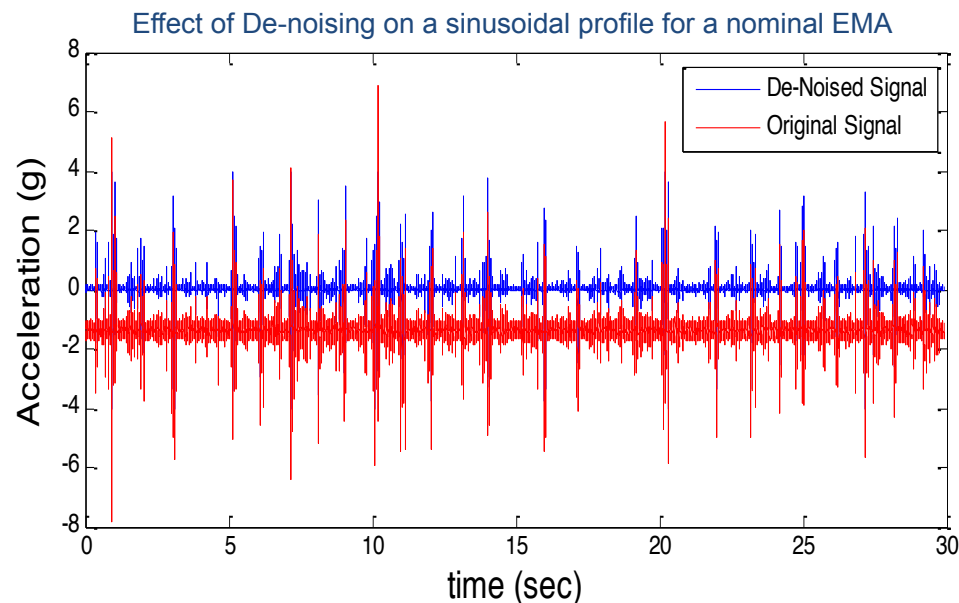
# Symbol Generation

- Qualitative approach based on analysis of fault transients
- Magnitude and slope deviations from nominal behavior abstracted as + (increase), - (decrease), and 0 (no change) symbols
- Symbols generated using a sliding-window scheme similar to the Z-test
- Fault signatures are predictions of how the magnitude and slope of a measurement will deviate from nominal under each fault case
- Represented using symbol pair for measurement and slope
- Fault isolation performed by comparing observed measurement deviations to predicted deviations



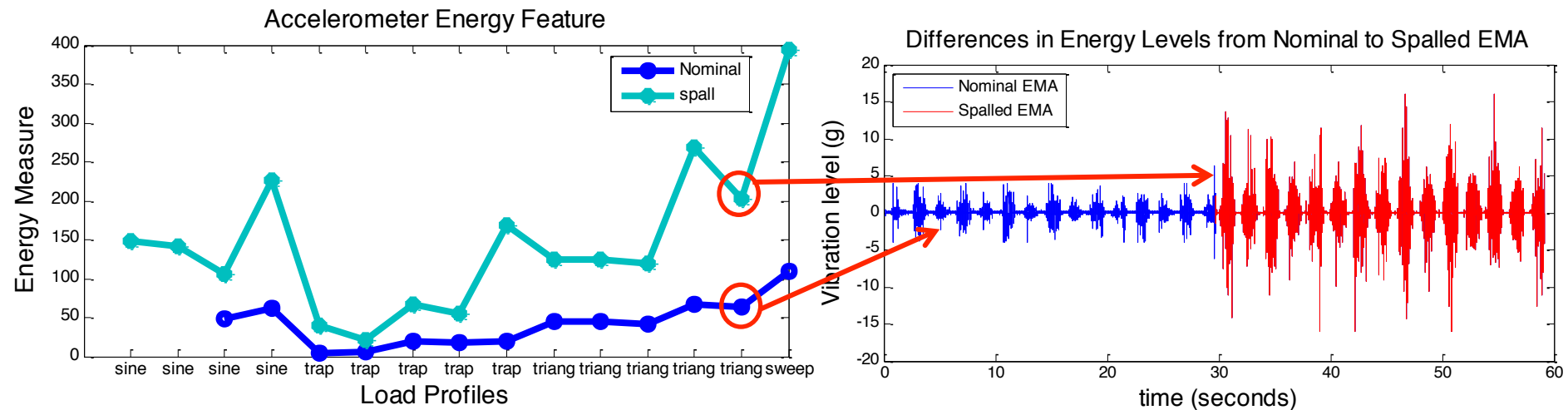
# Data-Driven Fault Disambiguation

- After an ambiguity set is obtained, the data-driven disambiguation module is triggered
- De-noising is carried out in real-time and appropriate features are computed
- Accelerometer data conditioning and de-noising is carried out by characterizing noise levels when actuators are stationary (e.g. during parts of trapezoidal profiles)
- Noise characterization constitutes determination of bias and noise variance



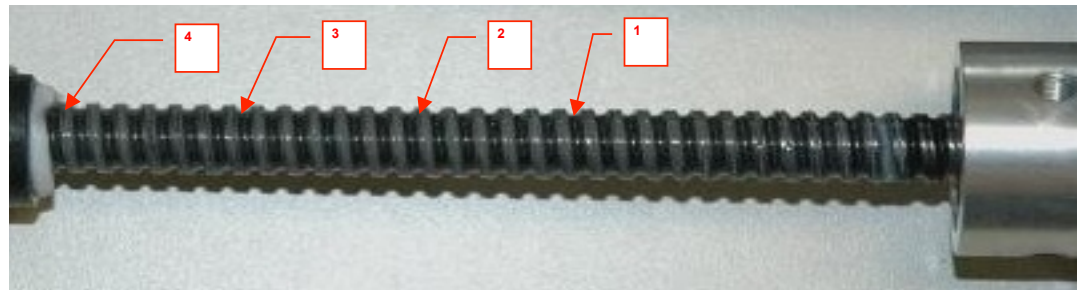
# High Speed Data Feature Extraction

- Average Signal Energy (ASE) used as the feature to distinguish between jam and spall faults
- The feature separates the jam and the spall faults well
  - Spall faults are significantly higher in energy than the corresponding nominal scenarios
  - Jammed actuator does not move easily, hence has lower vibration energy
- Depending on the motion profile and load levels the energy varies (inherently) between different operational profiles
- Features are normalized by a measure of this inherent energy
- Fault disambiguation success rate was ~90% (100% for spalls and 80% for jam faults)
- Due to noise some low energy jammed scenarios were not diagnosed



# Laboratory Experiments

- **Faults introduced**
  - Actuator ball return channel jam (discrete, abrupt)
  - Lead screw spall (continuous, incipient)
  - Motor failure (discrete, abrupt)
  - Sensor dead (discrete, abrupt)
  - Sensor bias & scaling (continuous, abrupt)
  - Sensor drift (continuous, incipient)
- **Profiles**
  - UH-60 Forward Primary Servo (collected in flight)
  - Laboratory experiments with a wide variety of motion and load profiles
- **Total experiments = 320**
  - Nominal = 134
  - Jam = 15
  - Spall = 15
  - Motor failure = 15
  - Sensor faults= 141



# Results – Diagnosis Accuracy

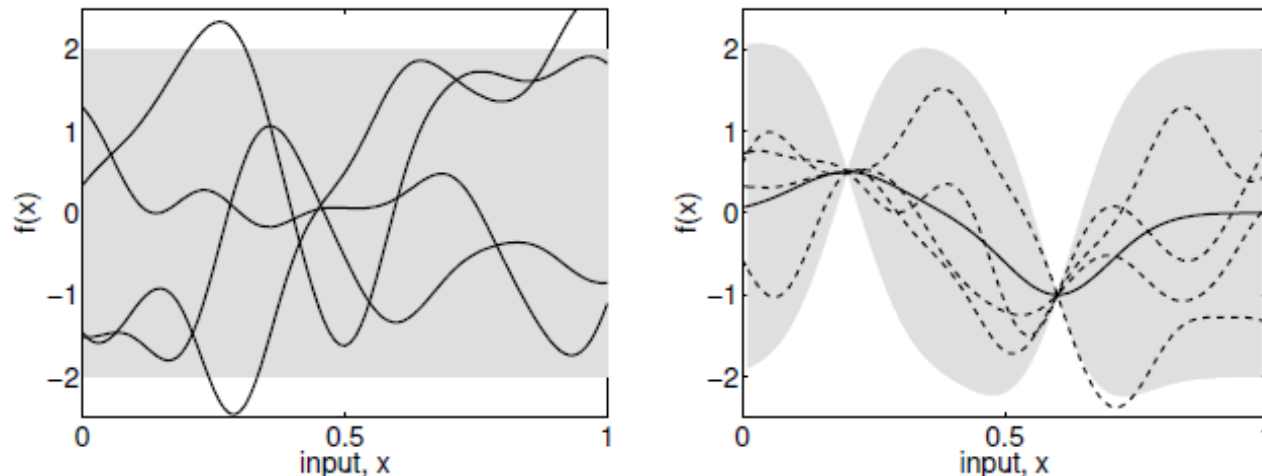
Fault Type	Total Scenarios	Correct Diagnosis	Diagnosis Accuracy
Nominal	134	133	99.25
Current Sensor Biased	15	15	100.00
Current Sensor Dead	15	15	100.00
Current Sensor Drift	15	15	100.00
Position Sensor Fault	21	13	61.90
Current Sensor Scaling	15	15	100.00
Ball Screw Return Channel Jam	15	10	66.67
Motor Failure	15	15	100.00
Lead Screw Spall	15	15	100.00
Temperature Sensor Bias	15	15	100.00
Temperature Sensor Dead	15	15	100.00
Temperature Sensor Drift	15	15	100.00
Temperature Sensor Scaling	15	15	100.00
<b>Total</b>	<b>320</b>	<b>306</b>	<b>95.625</b>

# Prognostic Algorithm

- Prediction algorithm: a Gaussian Process Regression (GPR) with neural network covariance function (with a noise parameter) was used

$$k_{NN}(x_i, x_j) = \sigma \sin^{-1} \left( \frac{\tilde{x}_i^T P^{-1} \tilde{x}_j}{\sqrt{(1 + \tilde{x}_i^T P^{-1} \tilde{x}_i)(1 + \tilde{x}_j^T P^{-1} \tilde{x}_j)}} \right)$$

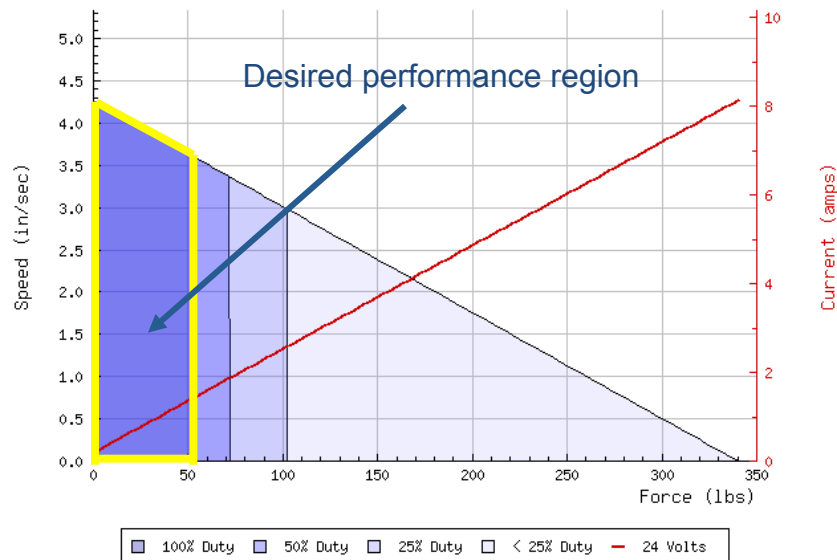
$$\tilde{x} = (1, x_1, x_2, \dots, x_d)^T, P = cI$$



- Results aggregated based on 50 runs with randomized training data selection and hyper-parameter initialization



# Prognostic Validation Scenario



Jam mechanism

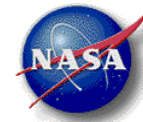
1. Jam was injected into the ball screw return channel of a test actuator on the FLEA
2. Performance region picked where a nominal actuator can operate continuously for extended periods of time (100% duty cycle)
3. Motion and load profiles were designed to stay inside this region – sine wave with 8 cm (3.15 in) peak-to-peak amplitude, 0.5 Hz frequency, and the following load levels: -50, +40, and +50 lbs
4. Motion was performed in 30 second intervals, with 15 second cool-down periods in-between
5. Current was limited to 6 amps @ 28 volt for the entire system at all times
6. Experiments were executed until actuator motors failed due to temperature build up and consequent windings insulation failure
7. Failure occurs at approximately 88 degrees C

Ball return jam  
(abrupt fault)

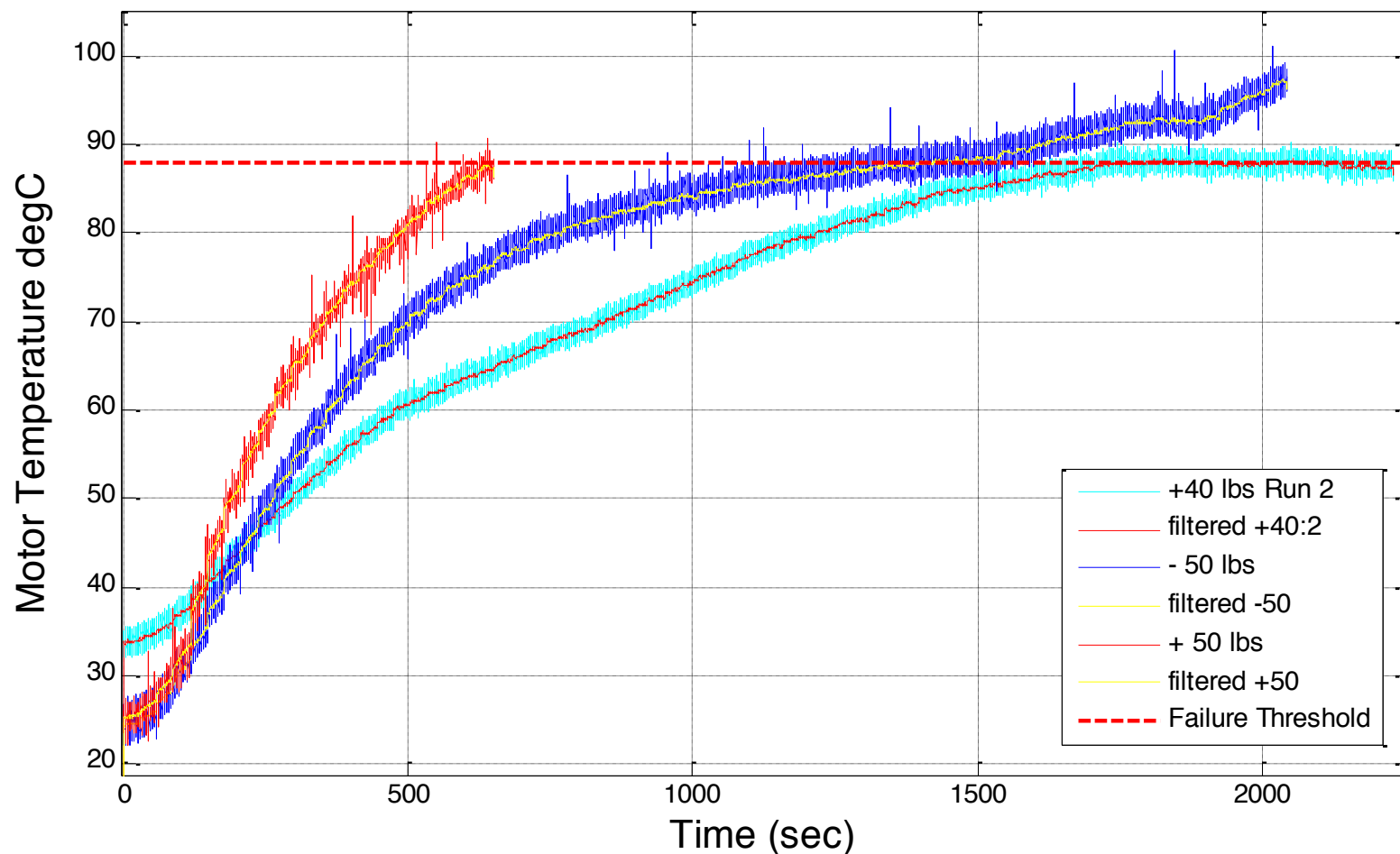
Heat build-up due to increased friction  
(cascading continuous fault)

Actuator failure due to  
motor windings short

# Run-to-Failure Experiments

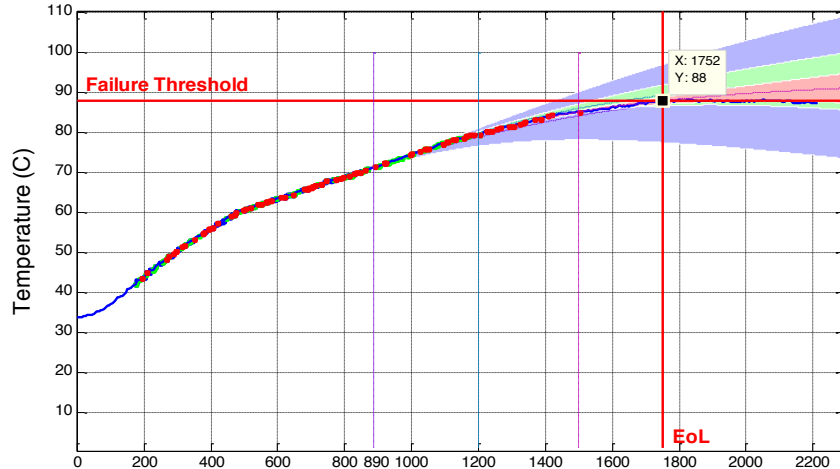


EMA Run-to-Failure Data

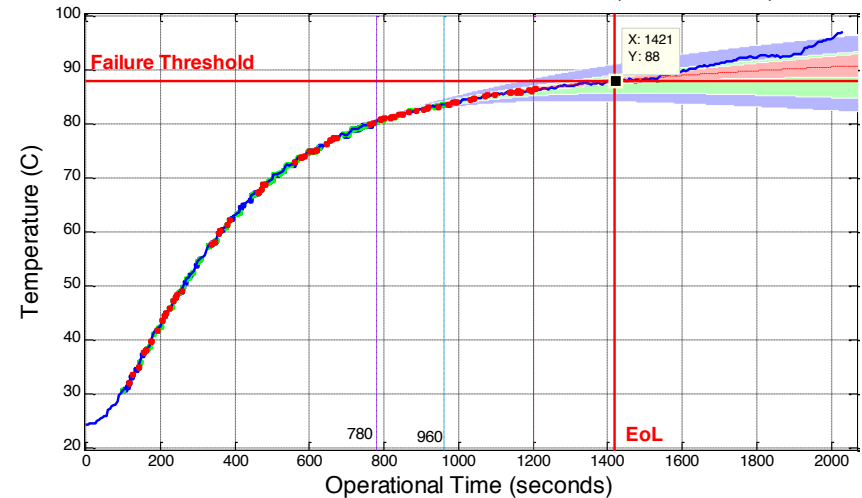


# End of Useful Life Prediction Results

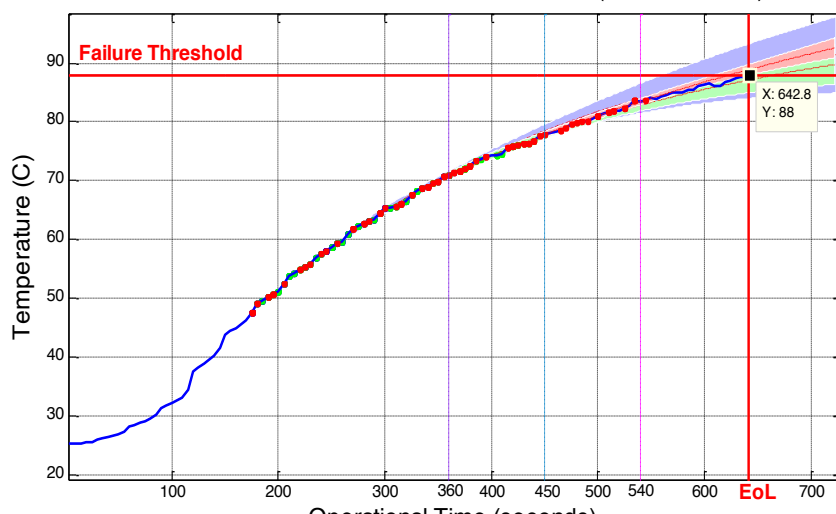
Life Prediction for EMA under Load Level 1 (+40lbs sine36)



Life Prediction for EMA under Load Level 3 (-50 lbs sine51)



Life Prediction for EMA under Load Level 2 (+50 lbs sine50)



**Fail threshold = 88C**

**Onset of detectable damage: 40C**

**+40 lbs sine36 Load Condition**

**$t_{p1} = 890$  MAPE = 6.62%;  $2\sigma = 215s$**

**+50 lbs sine50 Load Condition**

**$t_{p1} = 360$  MAPE = 4.76%;  $2\sigma = 60s$**

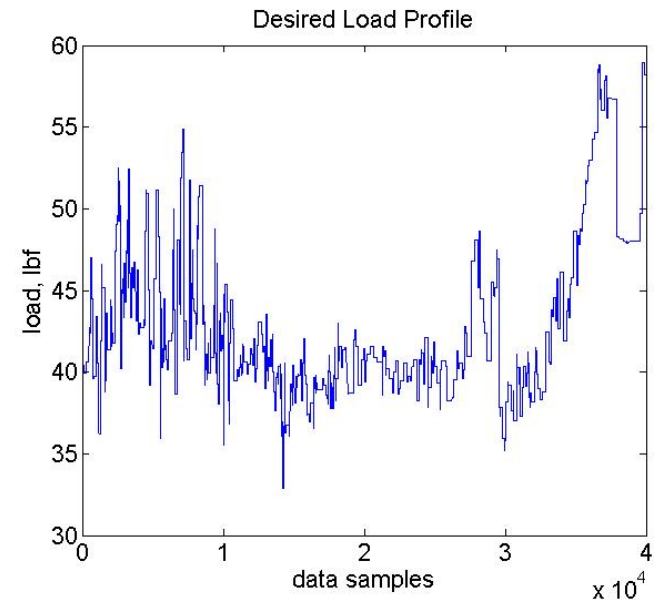
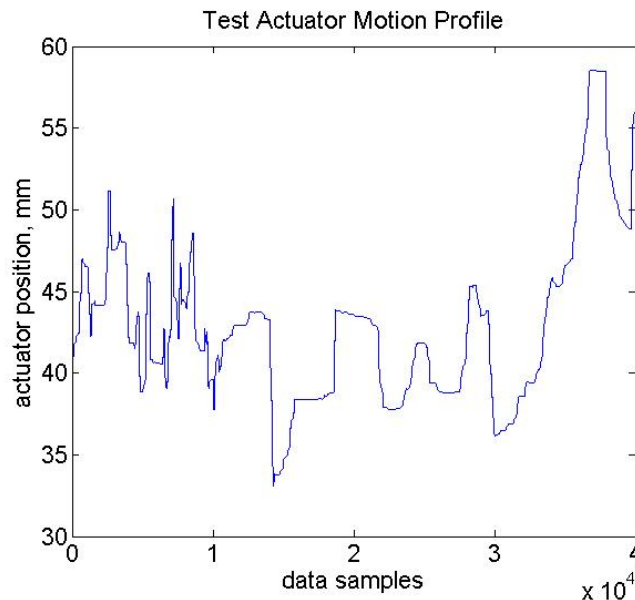
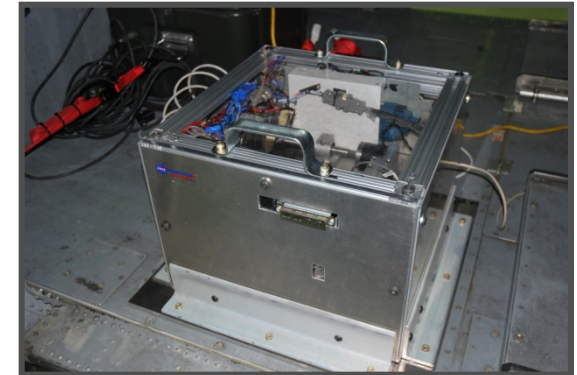
**-50 lbs sine51 Load Condition**

**$t_{p1} = 890$  MAPE = 8.02%;  $2\sigma = 338s$**

\* Colored bands around the predictions on the right-hand plots are the  $2\sigma$  bounds

# Flight Tests on UH-60 Black Hawk Helicopters

- Spall and ballscrew jam faults injected into the test actuators
- Improved data acquisition system tested
- Diagnostic system tested
- Some prognostic experiments executed



# Recent progress

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- Diagnostic and prognostic algorithm improvements
- Hardware improvements:
  - New accelerometer signal conditioner
  - Winding shorts simulator
  - Robustness improvements
- Sensor fault experiments
  - Position sensors (stuck)
  - Temperature sensors (bias, scaling, drift)
  - Current sensors (bias, scaling, drift)
  - Hundreds of fault scenarios with different parameters performed

- Hardware testbeds, for both laboratory and flight environment, have been developed
- Prototypes of a hybrid diagnostic system and a GPR-based prognostic system created
- Various types of fault modes injected, both in software and hardware
- Tests performed to validate performance in nominal and fault-injected scenarios
- Experimental data is available on NASA Ames DASHLink website:

<https://c3.ndc.nasa.gov/dashlink/>

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Thank you!